CHARACTERIZATION OF VINEYARD'S CANOPY THROUGH FUZZY CLUSTERING AND SVM OVER COLOR IMAGES

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Abstract

In this work we propose an image acquisition and processing methodology (framework) developed for performance in-field grapes and leaves detection and quantification, based on a six step methodology: 1) image segmentation through Fuzzy C-Means with Gustafson Kessel (FCM-GK) clustering; 2) obtaining of FCM-GK outputs (centroids) for acting as seeding for K-Means clustering; 3) Identification of the clusters generated by K-Means using a Support Vector Machine (SVM) classifier. 4) Performance of morphological operations over the grapes and leaves clusters in order to fill holes and to eliminate small pixels clusters; 5) Creation of a mosaic image by Scale-Invariant Feature Transform (SIFT) in order to avoid overlapping between images; 6) Calculation of the areas of leaves and grapes and finding of the centroids in the grape bunches.

Image data are collected using a colour camera fixed to a mobile platform. This platform was developed to give a stabilized surface to guarantee that the images were acquired parallel to de vineyard rows. In this way, the platform avoids the distortion of the images that lead to poor estimation of the areas.

Our preliminary results are promissory, although they still have shown that it is necessary to implement a camera stabilization system to avoid undesired camera movements, and also a parallel processing procedure in order to speed up the mosaicking process.

Key words: Fuzzy Clustering, vineyard, segmentation, SVM.

1. Introduction

In recent years several studies, based on image processing, have been conducted in order to assess features from the vineyard’s canopies (Meunkaewjinda et al., 2008, Berenstein et al., 2010, Brown et al., 2010, Nuske at al., 2011, Dey et al. 2012).

These studies are carried out in order to quantify features such as leaves, vine shoots, trunks and grapes areas, because this information allows, for example, to predict yields and quality, to perform smart sprayings or to determine the vineyard's vigor.

However, previous researches are aimed at solving one problem at a time, because these kinds of algorithms usually are time consuming and are unfeasible in real time.

Correa et al. (2012) demonstrates the feasibility of characterize (identify and to quantify) vineyards in real time, with performances near to 95%.

This approach combines FCM-GK with K-means to classify pixels, and an Artificial Neural Network (ANN) to identify them. Although has good results, these approach can be speeded up, and its identification performance improved, using SVM instead ANN.

Also, we propose to lead with the problem of image overlapping, which induces an error in the areas quantification.

Based on this approach, we present a framework that allows to characterize vineyards.

2. Methodology

In this section we will explain the steps that conform the framework, its theoretical background and its implementation.

2.1. Algorithm Description.

Steps that conforms the framework can be summarized as follow:

Step 1. Image acquisition: A set of vineyard's canopy images were photographed every 0.4 m using a digital camera Canon model 550D. Images were taken normal to the canopy, 1 m from row axis and 1.1 m aboveground.

A white screen was placed behind the canopy to avoid confounding effects from background vegetation. Images were captured at a resolution 2592x1728 and after that reduced to 800x600 and 480x320.

A routine for the image acquisition was created in Matlab 2010a and running in the main process called Clustering Process (Fig. 1).

Step 2. Color space and channels selection: Images were transformed to L*a*b* colors space, and the a* and b* channels used for the clustering process. Channel L* was eliminated to avoid the lightning effects. Channels a* and b* were selected, because they keep the chromatic information and brings a better performance in vineyard images segmentation (Correa et al. 2011).

Step 3. Initial clustering: A fuzzy clustering algorithm was applied to the channels a* and b*. Specifically Fuzzy C-Means with Gustafson-Kessel algorithm (FCM-GK) was selected due to their advantages when applied under agricultural field conditions (Correa et al. 2011). The number of cluster (eight) and all the algorithm parameters was set like in Correa et al. (2012).

This process is called Seeding Process and was implemented in an executable file developed in Matlab 2010a. This program reads the last image and generate as output, a text file with the eight centers.

Step 4. Secondary clustering: Cluster centers generated by FCM-GK are read from the text file (created in Step 3) and used as seeds for K-means in order to accelerate the convergence of the K-means and also to introduce a slant on the new processed images.

The seeding was updated every ten images in order to avoid bias produced by the canopy variations. To do that, the Seeding Process was running parallel to the main process also called Clustering Process (Fig. 1).

Step 5. Cluster identification: In order to identify the clusters generated by K-means a learning methodology called SVM was implemented. SVM was trained using 10 images and tested with 40. This learning methodology was implemented by a routine created in Matlab 2010a using the Bioinformatics Toolbox.

Step 6. Morphological operation: An image close operation was performed in order to fill holes inside the cluster; also clusters with areas less than 10 pixels were eliminated. A routine to perform this task was implemented and running in the Quantification Process.

Step 7. Creation of a mosaic image per row by Scale-Invariant Feature Transform (SIFT) in order to avoid overlapping between images. Also implemented in Matlab 2010a and running offline (Quantification Process), because is not required in real time.

Step 8. Area quantification: The mosaic image created in the Step 7 was split in 1m wide image. Every image was processes to determine the area of leaves and grapes as a percentage of the total image area; the number of pixel was counted and divided by the total number of pixel on the image. Also running in the Quantification Process.

2.2. Algorithm Implementation

In order to assess the feasibility and performance of the framework, a set of routines were developed in Matlab 2010a ®.

A schema of the implementation of the framework is depicted on Fig. 1.

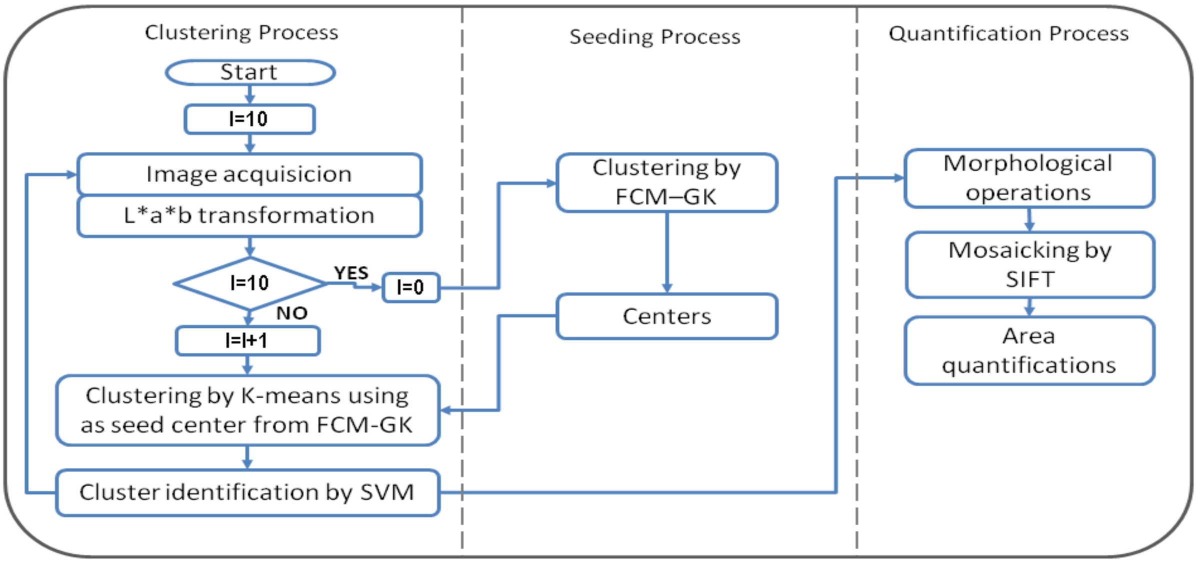


FIGURE 1: Flowchart. Note that there are two parallel processes, Process 1 and 2; the process three is an offline process.

The goal of this framework is to solve several problems simultaneously e.g. localized pesticide application. In this case, SVM can determine where the grapes are located and command, in real time, the aperture/close of a control valve. But still has the capability to compute (offline) the areas of grapes and leaves to be used on the yield assessment.

2.3. Theoretical Background

In this section we provide an overview of the algorithms used in our methodology:

- Gustafson-Kessel Clustering: The main feature of the Gustafson-Kessel (GK) algorithm is the local adaptation of the distance metric to the shape of the cluster by estimating the cluster covariance matrix and adapting the distance-inducing matrix correspondingly (Graves et al., 2007). The FCM-GK algorithm is based on iterative optimization of an objective functional of the c-means type:

$$J_m(U,V) = \sum_{i=1}^{c} \sum_{k=1}^{n} u_{ik}^{m} \, d_{ikA_i}^2 \tag{1}$$

The distance norm d_{ikAi} can account for clusters of different shapes in one data set:

$$d_{ikA_i}^2 = (x_k - v_i)^T A_i (x_k - v_i) \tag{2}$$

The metric of each cluster is defined by a local norm-inducing matrix A_i, which is used as one of the optimization variables in the functional. This allows the distance norm to adapt to the local topological structure of the data (Babuka et al., 2002).

The main drawback of this algorithm is that needs long runtimes compared against K-Means.

- K-Means: K-Means is by far the most popular clustering algorithm used in scientific and industrial applications this clustering technique that seeks to minimize the distance between points in the same cluster. K-Means is significantly sensitive to the initial randomly selected cluster centers. So although it offers no accuracy guarantees, its simplicity and speed are very interesting in real world applications.

- SVM. Classical learning systems like ANN suffer from their theoretical weakness, e.g. back-propagation usually converges only to locally optimal solution. So, to solve this problem appears SVM, that always finds a global minimum, and is less prone to overfitting (Kotsiantis, 2007), reason why we decide to use SVM instead ANN as used in Correa et al. (2012).

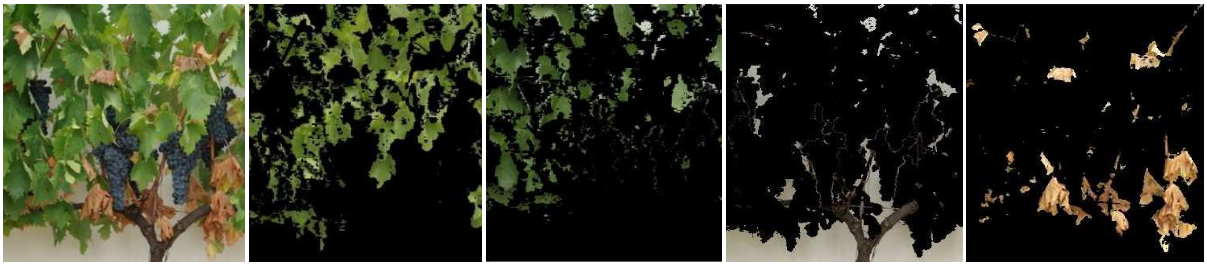
SVMs classify data by determining a set of support vectors, which are members of the set of training inputs. In the case of non-linearly separable input space, data inputs can be mapped to another high dimensional feature space that the data points will be linearly separable.

SVMs provide a generic mechanism to fit the surface of the hyper plane to the data through the use of a kernel function. The most common are: Linear or dot product, Quadratic, Gaussian Radial Basis, Polynomial and Multilayer Perceptron. In our case, we use the Polynomial kernel (order 3).

- SIFT. Scale-invariant feature transform, is a method for extracting distinctive invariant features from images that is used to perform reliable matching between different views of an object or scene (Lowe, 2004). The features are invariant to image scale and rotation, and are shown to provide robust matching across a substantial range of affine distortion, change in 3D viewpoint, addition of noise, and change in illumination. So, it's very suitable to matching vineyard images and creates mosaics of the entire rows.

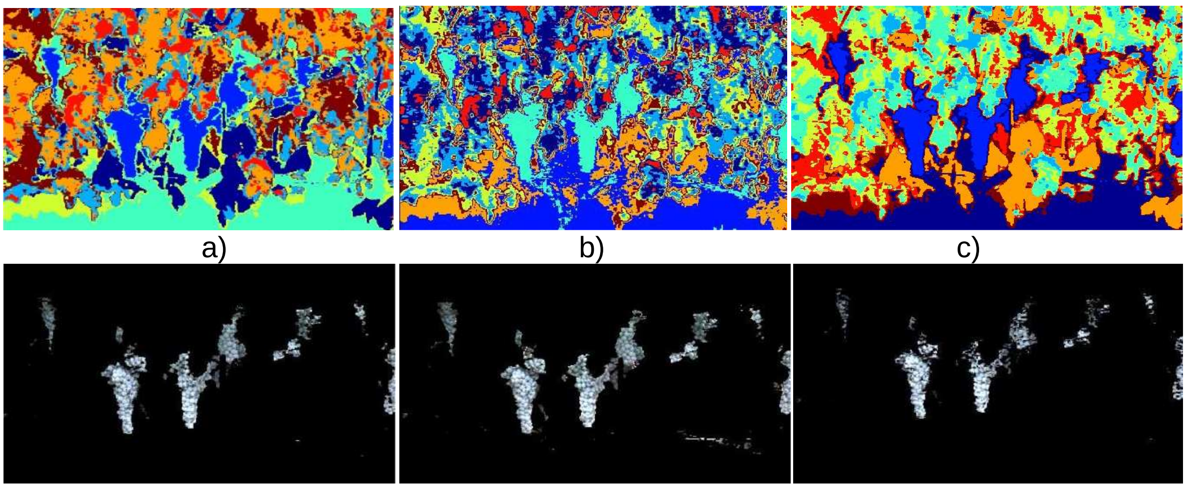
3. Results

In this section we will show how the algorithm performance, misclassification and runtime when K-means is seeded with the cluster centers generated by FCM-GK. One image was selected as example of the clusters generated and their results depicted on the Fig. 2.



a) b) c) d) e)

FIGURE 2: a) Original image (RGB). b) New leaves. c) Old leaves. d) Trunk and background. d) Dry leaves



d) e) f)

FIGURE 3: a) Classification by FCM-GK. b) Classification by Standard K-means. c) Classification by K-means seeded by FCM-GK. d) Grapes cluster generated by FCM-GK. e) Grapes cluster generated by standard K-means. f) Grapes cluster generated by K-means seeded by FCM-GK.

FCM-GK, K-Means without seeding and K-means with seeding, were evaluated using L*a*b* color space (channels a* and b*) and its performance depicted on the Fig. 3.

As shown in Fig. 3a, FCM-GK has a very good performance (97 %) as compared with K-means with random seeding (88%) Fig. 3b. Also Fig. 3c and f) shows a significant improvement when the centroids generated by FCM-GK are used as seeds for K-means (95%). A 7% of improvement (from 88% to 95%) is obtained in clustering performance when the seeding is performed.

So, the K-means with seeding have a similar performance to FCM-GK but with the advantage of a lower runtime. Indeed, one order of magnitude from 7 s to 0.7 s.

Depicted in the Fig. 4 a mosaic created by SIFT, using image acquired every 0.5 m, with a resolution of 800x600 pixel. When less resolution was used, wasn't possible to make feature matching.

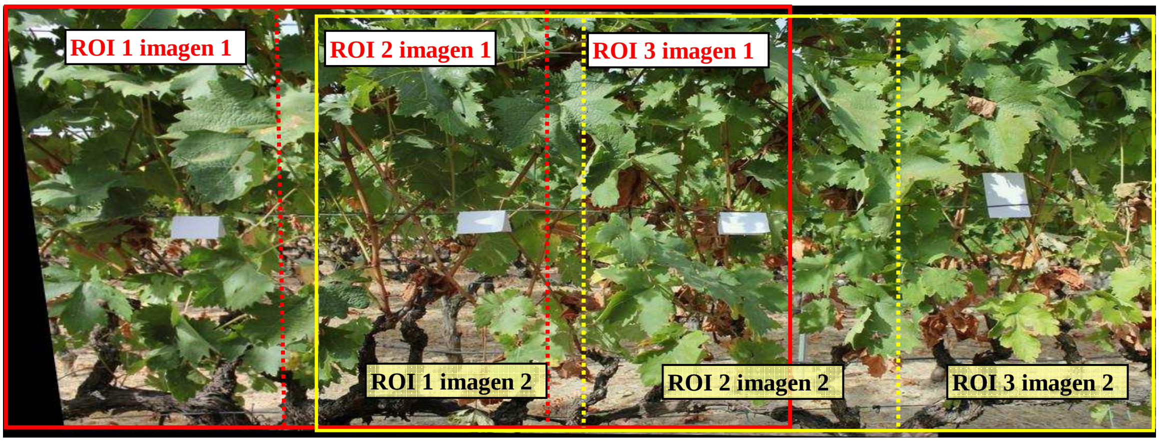


FIGURE 4: Example of mosaics generated by SIFT. White papers were located every 0.5 m as reference marks.

Every image takes a row segment of 1.5 m and when is fused with next image, create a new image of 2 m. Several test were carry out in order to determine the minimum overlaping needed to create a mosaic using SIFT. Because, images were acquired parallel to the vineyard there is a big change on the features present in the image. Thereby, was necessary to take one image every 0.5 m to guarantee the effectiveness of SIFT algorithm.

In order to speed up the algorithm performance, images were divided in three sections, (region of interest, ROI) of 0.5 m wide by 1 m height. SIFT is applied to ROI 2 of the image 1 and to the ROI 1 of the image 2. If no features matching are founded, SIFT is applied to the ROI 3 of the image 1 and to the ROI 2 of the image 2 as the Fig. 4 shows.

SVM, has shown to be a 100% positive detection for the grapes cluster and in less than 2 ms. But due to SVMs is a binary classifier, was necessary to train other SVM specific for leaves identification, with the same performance, like in the grapes cluster.

4. Conclusion

Other research like, Nuske et al. (2011) and Berenstein et al. (2010) have results near to 98% in the first case, but with 25% of false positive and performed offline. The second case has a 90% of grapes well detected, but don't deal against the image overlapping. Finally, Braun et al. (2010) deals with the image overlapping, but aimed only to assess leaves location. So our framework improves the state of the art, performing several task but in real-time.

A significant improvement on the runtime and also in the performance of K-means was achieved using our seeding strategy. Moreover, a reduction in the classification bias was reached through the update of the seed every ten images.

The SVM allows the identification of a 100% of the leaves and grapes in less than 3 ms. It`s a significant improvement against the ANN that needs 30 ms. Hence is very suitable for this application even the training could be performed on the field, because takes just 5 s.

Finally, our effort will be concentrated on speed up the whole framework, to reach a operational speed of 3 ms^{-1} and also in a camera stabilization system, to avoid vibrations and image deformations.

5. Acknowledgment

This research has been carried out in the LPF-TAGRALIA group at Dept. of Agricultural engineering of the Technical University of Madrid was also supported by the project Multisensory Fusion for Feature Extraction in Vineyards

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